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Natural Disasters and Spatial Heterogeneity in Damages: The Birth, Life and Death of Manufacturing Plants

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Abstract

In this paper we use the 1995 Kobe earthquake as a natural experiment to examine the impact of a large exogenous physical shock on local economic activity. For the first time we are able to control for local spatial heterogeneity in the damage caused by a natural disaster using geo-coded plant location and unique building-level surveys. In a survival analysis of manufacturing plants our results show that building-level damage significantly affects a plant's likelihood of failure and this effect persists for up to seven years. Further analysis demonstrates that the plants most likely to exit as a result of earthquake damage are the least productive which is suggestive of a cleansing effect as the average productivity rate of the remaining plants increases. We also find that continuing plants experience a temporary increase in productivity following the earthquake consistent with a "build back better" effect. In terms of local regeneration our results indicate that plant births increase in areas with more severe damage consistent with redevelopment plans for Kobe.

JEL: Q54, R10, R12, D22, L10, L25, M13, C01

Keywords: Earthquake, natural disaster, survival analysis, productivity

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1. Introduction

Earthquakes, like all natural disasters, can have a devastating impact on infrastructure, households, and firms in the affected areas. While humanitarian support is the immediate priority, in the medium to long term it is important for policymakers to understand how natural disasters impact local economic activity so they can provide the most effective support to affected communities.

The purpose of this paper is to examine the impact of the 1995 Kobe earthquake on local economic activity. The 1995 Kobe earthquake was one of the most severe in modern history, with a magnitude of 7.2 on the Richter scale and estimated to have caused $100 billion in damage (approximately 2.5% of Japan's GDP at the time).[1] The first contribution of this paper is to demonstrate the importance of capturing the spatial heterogeneity in damage that can result from a natural disaster. More specifically, we use building level surveys from the Japanese and Kobe City governments to measure the damage caused by the earthquake to individual buildings. The creation of this unique dataset enables us to capture the degree of heterogeneity in damage levels which can leave a building undamaged while totally destroying neighboring buildings. Our second contribution is to combine our unique building-level damage variable with a 16 year exhaustive panel of plants both before and after the earthquake to examine the impact of the earthquake on the birth, life and death of plants with an emphasis on plant-level productivity. Specifically, we answer four related questions. First, do building level damages have a prolonged effect on the probability of plant survival and, second, is there evidence of a cleansing effect associated with natural disasters whereby the least productive firms are most likely to exit? Third, do surviving firms increase their productivity consistent with a "build back better" effect? Finally, is the location of plant births affected by the extent of the damage to a local area?

The premise that natural disasters may have a cleansing effect has its origin in a number of theoretical studies, such as Caballero and Hammour (1994) and Ouyang (2009) who have suggested that it is the least productive and the youngest firms which fail as a result of a recession. To date the empirical evidence on how cost shocks induced by recessions may hasten the demise of unproductive firms has been rather mixed (see, for example, Barlevy 2002). In this regard, our study can be viewed as a natural experiment where a large number of firms are subject to a substantial exogenous shock (with both supply side and demand side implications)

[1] Although officially known as the Hanshin-Awaji Great Earthquake it is also known as the Hanshin or Kobe earthquake. In this paper we follow Horwich (2000) and refer to it as the Kobe earthquake.

that was unrelated to their productivity prior to the event.[2] The Kobe event therefore provides an ideal setting to examine the short and medium term effects of a negative shock at the local level. Importantly for our study, Kobe is an area of Japan which was believed to be relatively safe from earthquakes and hence little preparation and anticipatory behaviour took place prior to the earthquake. From an empirical perspective it can therefore be considered a truly exogenous shock.[3]

A brief review of the existing literature shows that a common trait in many studies is the use of aggregated data whether it is across sectors, space or disaster-type. The majority of studies tend to take a cross-country macroeconomic approach to determine the impact of a disaster on country level growth (e.g. Loayza *et al.* 2012, Noy 2009, Strobl 2012 and Ahlerup 2013). The results from these studies have been rather mixed. On the one hand, because natural disasters are often associated with significant physical damage and human suffering the impact should be "naturally negative" (Felbermayr and Gröschl, 2014). On the other hand, fiscal expenditure and foreign aid can stimulate locally affected areas and result in an overall positive effect driven by a disaster response that may result in more effective infrastructure or an increased productive effort in unaffected areas (Albala-Bertrand 1993). Likewise, when more capital is destroyed than labor, the return to capital can increase which can also result in short-term growth. Local workers may also be incentivised to work harder to compensate for inter-temporal losses (Melecky and Raddatz 2011).[4]

Other research has raised concerns about the aggregation effect. Loayza *et al.* (2012) for example, show that the type and magnitude of a natural disaster can determine the sign and size of the estimated effect. Using satellite derived nightlight data, Bertinelli and Strobl (2013), Strobl (2011) and Elliott *et al.* (2015) show that for hurricanes and typhoons, national level regressions can mask much of the impact at the local regional level. Similarly, Fisker (2012) using an

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[2] The earthquake can be thought of as a traditional cost shock (the cost of rebuilding the plant and/or replacing workers who may have been killed or migrated from Kobe) or a demand and supply shock. On the demand side, disruption to customers as a result of the earthquake may mean delays to the purchase of intermediates. On the supply side, plant production may be delayed whilst repairs are undertaken which, for a given plant, may lead to a loss of market share to undamaged competitors elsewhere in Kobe or further afield both within Japan and internationally.

[3] The unanticipated nature of the shock is emphasised by Kaji Hideki (UNRCD Director) who stated that "*During the 1,500 years that earthquake occurrence has been recorded in Japan, not once has Kobe been directly hit by an earthquake and it has always had the image of being a city safe from earthquakes*". The unexpected nature of the earthquake is emphasised by Ederington (2011) who, when discussing the lack of insurance states that *"Few businesses or private households held earthquake insurance. Indeed, most losses were uninsured: only 3% of property in the Kobe area was covered by earthquake indemnity*".

[4] The absence of a consensus on the average effects of natural disasters is illustrated by Cuaresma *et al.* (2008) and Cavallo and Noy (2011) who argue that on average natural disasters have a positive and negative impact, respectively. In a related literature, Davis and Weinstein (2002) and Brakman *et al.* (2004) examine the effect of allied bombing during the second world-war on city size in Japan and Germany, respectively. They find the effects of such bombing to be short term with long run city size unaffected.

earthquake intensity measure finds that although there were no observable country-level effects, an earthquake does have a significant negative impact at the local level. This may be particularly important for earthquakes as their local impacts tend to differ even within relatively small geographical areas in that the extent of damage to a location depends on the magnitude, depth, and distance to the epicentre but also on local geological conditions, that can differ across just meters, and the architecture of buildings.[5] Finally, and perhaps most importantly for our paper, one of the main impediments to accurately measuring the impact of a natural disaster has been the lack of a precise proxy for damage. That is, studies have almost exclusively resorted to using (possibly systematic) measurement error prone post-disaster cost estimates (most of the macro-economic studies have relied on the EMDAT database which collects information on losses due to natural disasters at the country level from publicly available sources) or, more recently, potential destruction proxies derived from physical characteristics of the event.[6]

A handful of other papers use firm or plant-level data to examine the impact of natural disasters. For example, Craioveanu and Terrell (2016) consider the impact of storms on firm survival using elevation above sea level as a measure of flood damage during Hurricane Katrina and find that large firms and those with less damage are more likely to survive. Other studies of Hurricane Katrina use geo-coded categorization of wind and flood damage information to capture heterogeneity in the damage (see e.g. Jarmin and Miranda 2009 and Groen *et al.* 2016). Paxson and Rouse (2008) for example use the variation in standing water in residences to predict return migration of refugees to New Orleans after Hurricane Katrina. De Mel *et al.* (2012) conduct a post-disaster field study of surviving enterprises and workers following the Sri Lanka tsunami and find that aid helps retailers, but not manufacturing firms, to recover. Hosono *et al.* (2012) investigate the effect of banks' lending capacity on firms' capital investment using the Kobe earthquake as an exogenous shock but measure damage only broadly in terms of affected areas. Finally, Tanaka (2015) examines the short-term economic impact of the Kobe earthquake but does so by assuming that all plants within Kobe suffered the same damage. He finds that the earthquake had a significant short term impact on employment and value added.

Other studies of the Kobe event include duPont *et al.* (2015) and duPont and Noy (2015). The first paper estimates the long term socio-economic impact of the earthquake using city and town

[5] The heterogeneous nature of earthquake damage relates to the presence of possible landslides, fires, soil liquefaction, floods and tsunamis. Two important geological factors are the softness of the ground and the total thickness of the sediment which can vary widely even within several meters of an area.

[6] Other studies that attempt to capture the impact of a natural disaster include Okazaki *et al.* (2011) who use broad geographical damage indicators to examine the 1923 Great Kanto earthquake and Felbermayr and Gröschl (2014) who build a database of disaster events and intensities from primary geophysical and meteorological information.

data using a synthetic control method to create a counter-factual. The results suggest a permanent negative average income effect for areas close to the epicentre but also some evidence of a positive impact in the surrounding areas. The second paper also uses synthetic control methods (following Abadie *et al.* 2010) to measure the long term impact of the Kobe earthquake and suggests that the true cost of the earthquake was twice as high as previous estimates.[7]

Our contribution to the literature is to capture the degree of damage to the buildings of individual plants and then to assess how damage levels affect the birth, life and death of plants. Our methodological approach is to begin with a simple productivity decomposition approach (Foster *et al.* 2006) to help understand how the Kobe earthquake may have acted as a driver of productivity change. Next we employ a proportional hazards modelling approach (Cox 1972) to estimate the impact of building-level damage on plant survival.[8] For the surviving firms we then estimate a simple panel fixed effects model of the determinants of productivity. Finally, we estimate a negative binomial model to investigate the determinants of plant birth location taking into account measures of damage to local georgraphical areas.

To briefly highlight our results, our decomposition analysis shows that improvements in productivity over our sample period are driven predominantly by the entry of new plants after the earthquake. In terms of plants that existed prior to the earthquake we find that, as we might expect, plants that experienced building damage were less likely to survive than those residing in less damaged buildings but, more surprisingly, we find that the reduced probability of survival lasts for up to seven years after the earthquake. This suggests that plants can continue to suffer from the negative effects of a natural disaster for much longer than the conventional macroeconomic evidence suggests. We also find that the risk of exit as a result of earthquake damage is highest for those plants that are the least productive which is supportive of a cleansing effect from large cost shocks. In terms of plant performance, our panel fixed-effects results show a positive effect of building-damage on post-quake labor productivity albeit with a fairly rapid decline over time which is indicative of a narrative where surviving plants "build back better". Finally, for plant births, our results suggest that low to moderate levels of earthquake

[7] Other studies that examine different aspects of the Kobe earthquake include Sawada and Shimizutani (2008) and Fujiki and Hsiao (2013). There have also been a small number of case studies examining US disasters such as Dorfman *et al.* (2007) who look at the employment and wage effects of Hurricane Katrina. A second strand of the literature examines the impact of earthquakes on the housing market following an earthquake (Beron *et al.* 1997 looking at the 1989 Loma Prieta earthquake and Deng *et al.* 2013 looking at the 2008 Wenchuan earthquake).

[8] There is a large literature examining different aspects of firm survival. For example, Agarwal and Gort (2002) study firm survival in the context of a product life cycle framework while Audretsch and Mahmood (1995) use a hazard function to examine new firm survival rates.

damage, in relatively small geographical areas, generally deter such births, while more severe damage appears to have acted as a positive stimulus for new plant creation. Reconstruction and government support is the most likely explanation for these results.

The reminder of this paper is organised as follows. Section 2 presents the background to the Kobe earthquake. Section 3 describes our data. Section 4 presents our decomposition methodology and results. Sections 5, 6 and 7 we present our analysis of plant exit, plants that continue and plants that enter Kobe after the earthquake. Section 8 concludes.

2. The Kobe Earthquake

The 1995 Kobe earthquake occurred at a time when the Japanese economy was in a period of stagnation following the economic boom of the 1980s. During the 1990s and 2000s the Japanese economy grew very little and due to a historic reliance on traditional industries such as steel and shipbuilding the city of Kobe faced considerable challenges. This also meant that the local Kobe government had to incur considerable debt to pay for the city's reconstruction. Johnston (2005) points out that by the end of 2005 the City of Kobe had more than 3 trillion Yen in municipal bonds outstanding and was effectively bankrupt. Since firms also took on considerable borrowings following the earthquake they too came under financial pressure due to the relative slow growth of the Japanese economy. Hence, the effects of natural disasters can be prolonged and affect the chances of plant survival long after the event itself as the accumulated debt incurred to help the rebuilding process means that plants become less competitive relative to their undamaged and non-indebted competitors.[9]

The earthquake that shook the Hanshin region of Western Japan that includes the city of Kobe struck on the 17th January 1995 at 5.46am and lasted for a little under one minute with a strength of 7.2 on the Richter scale. Kobe is located 430 km southwest of Tokyo and at the time was an important port city with a population of close to 1.5 million contributing around 10% of Japan's total GDP (Orr 2007). The epicentre of the earthquake was 25km from central Kobe and was the first major earthquake to strike a Japanese urban area since the end of World War II. As a port city Kobe was home to a large number of working class and immigrant communities as well as a middle class involved in the shipping and industrial sectors. As an older city Kobe also

[9] This section draws in part on Edgington (2011), who examines the reconstruction of Kobe and the geography of the crisis, and a report from UNRCD (1995) entitled the "Comprehensive Study of the Great Hanshin Earthquake".

had a very high population density with between 6,000 and 12,000 people per square kilometre (Orr 2007).[10]

The massive scale of the destruction was caused by two key factors in addition to the magnitude, depth and timing of the earthquake. First, the soil in many areas of the city was soft and water saturated which led to landslides and structural damage as a result of liquefaction. This meant that damage was concentrated in a narrow area of soft soil 30km long and just 2km wide (Orr 2007). Second, Kobe itself is located on a narrow strip of land between the Rokko mountains and Osaka Bay which meant that city lifelines were easily cut not least because they were almost all installed prior to more recent building codes. Hence, immense damage was caused to infrastructure including the expressway and numerous high-rise buildings. In addition, tunnels and bridges were destroyed and train tracks buckled.

One consequence of the earthquake was the wholesale destruction of houses and commercial premises with large parts of the city affected by fires. Firestorms were a particular problem in the narrow streets of the older districts where the traditional wooden houses were still prevalent and tended to be populated by Kobe's older residents and students. The middle classes tended to live outside of the centre in higher quality and newer homes (Shaw and Goda 2004).

According to the City of Kobe (2012), 4,571 people lost their lives in Kobe city with a further 14,687 injured. A notable 59% of those who died were over the age of 60, the majority of whom died due to crushing related injuries. The damage to buildings was considerable. The number of fully collapsed buildings was 67,421 and partially collapsed 55,145. Fire damage caused the complete destruction of 6,965 structures with many others being partially burned (covering a total area of 819,108 m^2). Utilities were also severely impacted. In addition to city-wide power and industrial water failure, 25% of phone lines were down and 80% of gas supplies no longer operated. The total value of the damage was estimated to be around 6.9 trillion Yen (0.0681 trillion dollars in 2016 prices).

In terms of industry, according to the City of Kobe (2012) report, many large manufacturers suffered damage to their main factories and had production lines interrupted. For small and medium sized enterprises the damage was extensive. Approximately 80% of factories in the non-leather shoe industry were damaged and 50% of the Sake breweries were severely impacted. The tourism, agriculture and fishing sectors were also badly affected. The manufacturing production indices in September 2007 for non-leather shoes and Sake Breweries were only

[10] The housing in the older areas of Kobe tended to be constructed using heavy roof tiles and light frames and were designed to withstand storms but were not well suited for earthquakes (Orr, 2007).

78.8% and 40.4% of the September 1994 figures respectively suggesting a significant de-agglomeration effect (see e.g. Maejima 1995). Further difficulties were caused by the collapse of the Hyogo Bank in Kobe following bankruptcies from the bank's borrowers (individual and corporate) which in turn lead to a fall in local land prices which exacerbated problems of bad loans from other borrowers (Edgington 2011).

The one mitigating factor that helped the larger companies was their membership of wider conglomerates (Keiretsu) which had access to funds to enable rapid recovery. Examples include Kobe Steel, Kawasaki Steel and Mitsubishi Heavy Industries. However, small and medium sized enterprises were less fortunate. Edgington (2010) cites a Kobe Chamber of Commerce survey that found that for the first one or two years following the earthquake, large numbers of businesses and retailers were operating out of tents and prefabricated buildings with many others suffering continued financial problems that often resulted in the closure of the business (HERO 1998). Moreover, small and medium sized firms found it difficult to benefit directly from the large construction projects that were often lead by Tokyo headquartered corporate companies. According to Saito (2005) the most affected firms were those that were reliant on local demand and those that faced low cost competition from China.

Finally, in terms of reconstruction efforts, given the heterogeneous nature of the reconstruction expenditure both politically and geographically it is important to have an understanding of the decision making process. Although considerable effort was targeted at house building, neighborhood community reconstruction projects and health care, in this paper we are primarily concerned with economic revitalization. The main objectives according to the City of Kobe (2012) were to secure job opportunities through early recovery, to promote local industries that were perceived to be central to urban restoration, to create new businesses and to encourage growth industries to move to Kobe which would result in a more sophisticated industrial structure (build back better). Much of this work came under the Hansin-Awaji Economic Revitalization Organization which operated between December 1995 and March 2005. One specific policy that we are able to capture is where Kobe city nominated a number of areas (for three years) that were severely damaged in the quake but were perceived as being in strategically important areas of the city (Kobe City Office report "The emergency development regulation for earthquake disaster reconstruction").

Emergency measures provided by the government to firms included an emergency loan system (ended 31st July 1995) which provided 94.9 billion Yen in loans in 5,979 cases and a further 23.2 billion Yen in 4,129 cases for unsecured loans. Between 1998 and 2005 it was also possible to receive targeted loans and business guidance on how to re-open a business in Kobe. Other initiatives included a rental assistance scheme to operate in private factories and interest subsidies for small and medium sized businesses that wanted to invest in new equipment. Finally, to help attract new industries and international trade, the Kobe Enterprise Zone was approved in January 1997 which had attracted 374 firms by 2006.[11]

However, as Horwich (2000) points out, whilst the non-interest loans and subsidies for factory construction certainly helped, not all firms could get access to these funds leading to further bankruptcies. Whilst these loans were welcomed by business, and in many cases enabled the business to continue trading, the resultant increased debt burden was said to lead to many bankruptcies over the following 10 years (Edgington 2011).

To put the local economic impact of the earthquake in context we now turn briefly to the economy of Japan. During the 1990s Japan was in a period of stagnation following the boom of the late 1980s. The country experienced relatively low growth up until 2004/2005 when the recovery picked up. In Kobe the damage from the earthquake coupled with an industrial structure that relied on the traditional heavy industries of shipbuilding and steel, meant that recovery in certain sectors was challenging. This also meant that the City of Kobe had to incur considerable debt to continue to pay for the city's reconstruction. Johnston (2005) points out that by the end of 2005 the City of Kobe had more than 3 trillion Yen in municipal bonds outstanding and was effectively bankrupt. Since firms also took on considerable borrowings following the earthquake they too came under financial pressure due to the relative slow growth of the Japanese economy.

Overall, it can be argued that the Kobe earthquake had a substantial long-term impact on Kobe. Figure 1 provides manufacturing output in Kobe and for the rest of Japan, each expressed relative to 1993 pre-earthquake output. As can be seen, manufacturing output in Kobe remains below pre-earthquake levels throughout our sample period, with 2007 output being only 89.2% of pre-earthquake levels. Similarly, the Nikkei Weekly (2005) reported in 2005 that 69% of small firms claimed that their profits had not returned to pre-quake levels. However, these trends are not seen at the national level. As Figure 1 illustrates, national manufacturing output in the rest of Japan exceeded pre-quake levels as early as 1996. Throughout our sample period the rest of Japan fared better, relative to the immediate pre-quake period, than Kobe.

[11] In a related development the Port of Kobe had largely been redeveloped by the end of March 1997. However, the number of containers handled by the Port of Kobe in 2007 was still only 84.8% of the 1994 figure, although the total value of imports in 2007 was 106.4% of the 1994 value and exports were 95.3% of the 1994 value.

[Figure 1 about here]

3. Data

3.1 Panel Data of Manufacturing Plants

We utilise the Japanese Manufacturing Census (Japanese Ministry of Economy, Trade and Industry) and the Establishment and Enterprise Census (Japanese Ministry of Internal Affairs and Communications) to create a database of manufacturing plants in Kobe city from 1992. Our sample contains 4349 plants in 1992, falling to 2134 in 2007. Note that data for 1994 are missing from our dataset as the earthquake prevented data collection. This year is therefore omitted, through necessity, from our analysis. Importantly, the Manufacturing Census and the Establishment and Enterprise Census are exhaustive and do not have a minimum size requirement for inclusion. As such, we do not have the problem of plants leaving the sample simply because their size has dropped below a minimum threshold. We are therefore able to identify precisely when a plant closed down in Kobe. One caveat is that although we know when a plant closes and reopens elsewhere in Kobe, we cannot distinguish between those plants that closed permanently and those that moved elsewhere within Japan. However, since the focus of this paper is on the local impact of the Kobe earthquake, this distinction is not crucial. Whether a plant exits or relocates, its activities within Kobe have ceased. In terms of characteristics of the plants, the census provides, amongst other things, information on the exact address, sector of activity, age, average wages, employment, and value added.[12]

3.2 Earthquake Damage Data

3.2.1 Plant-Level Damage

To accurately identify the level of damage suffered by each plant we utilise the 'Shinsai Hukkou Akaibu' (archive on the damage of the 1995 Hyogo-Awaji earthquake) by Kobe City Office and Toru Fukushima (University of Hyogo), together with 'Zenrin's Residential Map, Hyogo-ken Kobe city 1995' from Toru Fukushima (University of Hyogo). These sources provide a highly detailed map of Kobe and assign one of five colors to each building to categorise damage. Shortly after the earthquake each registered building (registered prior to the earthquake) was

[12] In Japan an address usually consists of seven elements starting with a prefecture (*ken*) which is the largest division of the country. Next comes the municipality or city (*shi*). Each city consists of a number of wards (*ku*) which may be further divided into *machi* or *cho*. Below this are the detailed address information which is the city district (*chome*) followed by the city block (*banchi*) and finally the building number (*go*).

surveyed to measure the damage incurred and then used to classify the building into one of five categories:

1. Green: No damage (damage was not more than 3 per cent of the building's total value).
2. Yellow: Partially collapsed (damage between 3-20% of the building's value).
3. Orange: Half collapsed (damage between 20-50% of the building's total value; typically partial damage to the principal structures such as walls, pillars, beams, roof and stairs).
4. Red: Fully collapsed (damage between 50-100% of the building's total value; typically damage to the principal structures such as walls, pillars, beams, roof and stairs).
5. Pink: Fire damage (damage between 50-100% of the building's total value).

The original maps consist of 111 individual tiles in jpeg format covering the Kobe area. These were then geo-referenced and the buildings and their corresponding colors extracted and cleaned to generate a set of building polygons with their damage colors. Figure A in the online appendix presents an example of part of the original tiles. Using the address of each plant we are able to identify the plant's location by its latitude and longitude which enables us to assign each plant to an exact building which is then classified in to one of the five categories listed above.

As a starting point we create a single variable damage index, *PlantDAM,* which is a proxy for the percentage of loss in value of the building in which a plant was residing. More specifically, we assign a numerical scale to each building color type by using the median between the category thresholds (i.e. 11.5% loss of value for yellow, 35% for orange, and 75% for red), except for green buildings which we assigned a loss of value of 0%. As part of our robustness checks we experiment with other values for each category.[13]

3.2.2 Chome-Level Damage

From the original map the local authorities also created summary measures of damages at the local chome-level, where a chome is a small administrative unit (city district) of which there are 3,179 in the Kobe-Hanshin area.[14] Since we have a proxy for building-level damage it means that

[13] One could also use the individual categories on their own and create a set of corresponding dummy variables. We opt for the ratio variable as our benchmark proxy for a number of reasons. First, as will be seen, we include time interactions in our analysis, making the interpretation of a single index more amenable to both presentation and interpretation. Second, this allows us to have an index that is more easily compared to our geographical damage index which is derived from a different data source (described below). Nevertheless, in our sensitivity analysis we replace the single damage index with individual dummies for each damage level.

[14] Chomes vary greatly in size, ranging from a few hundred squared meters to several square kilometers. However, the majority of the manufacturing plants within Kobe are located in chomes that tend to be just a few hundred

we know the number of buildings for each chome categorized by damage color. This enables us to create a chome-level building damage indicator based on the percentage of damage to each building given by:

$$ChomeDAM_j = \frac{(w_{pink} \times pink_j) + (w_{red} \times red_j) + (w_{orange} \times orange_j) + (w_{yellow} \times yellow_j) + (w_{green} \times green_j)}{total_j} \qquad [1]$$

where the denominator, *total*$_j$, is the total number of buildings and *red, pink, orange, yellow,* and *green* are the number of buildings within chome *j* that are classified in each of these categories. The weights *w* are the loss in value associated with each color assuming that losses are the midway points between the thresholds (except for the green category where we assume no loss). We performed similar sensitivity checks to those employed for our building damage variables.

Figure 2 presents the distribution of our *ChomeDAM* index. One can immediately observe a wide variation in damages across individual chomes linked to geographical and building differences discussed in Section 2, as well as the unique ability of earthquakes to have very different impacts within narrowly defined areas. One implication is that the assumption of spatial homogeneity in earthquake damage even at relatively small geographical areas such as chome level, let alone the city level, as previous studies have used, may induce a considerable degree of measurement error and hence attenuation bias.

[Figure 2 about here]

Note that *PlantDAM* and *ChomeDAM* are zero prior to the earthquake and, for unaffected plants, after the earthquake. For affected plants they both take on positive value, depending on the extent of damages, for each year following the earthquake.

3.2.3 Other Damage Indicators

Previous studies in an attempt to identify spatial differences in earthquake damage have often used certain physical characteristics of the event such as distance to the epicentre or peak ground acceleration (Garmaise and Moskowitz 2009). We create similar proxies. More specifically, the

meters squared. In order to confirm the accuracy of our geo-referencing of buildings and their damage type we overlaid our building shape-file with a shape-file of the chomes, calculated the number of buildings *per se* and per damage category per chome and compared this to the official aggregated data available, we found these to match almost perfectly.

distance to the epicentre (*DISTEPI*) is calculated as the straight-line distance from the epicentre to the latitude and longitude of a plant's location. In our sample the average plant is 18.6 km from the epicentre with a standard deviation of 13.5 kilometres. To obtain a measure of peak ground acceleration we used the gridded shake map generated by Fujimoto and Midorikawa (2002) to allocate peak ground acceleration values to each plant's building which we call *SHAKE*.[15] Figure 3 shows the overall shake map for Kobe. Because the grids of the shake-map are fairly large we overlay this with the building damage map data shown in Figure 4. Figure 4 shows the high degree of heterogeneity of damages even within shake-map cells.

[Figures 3 and 4 about here]

3.3 Other Data

Although we know the level of damage of the building in which the plant is located, our dataset does not include building specific information on the type of construction. However, the local authorities did collect information on building characteristics at the chome-level. These include the number of buildings by year of construction and building construction types (brick, cement, wood and iron). We use these to calculate the average age of buildings in a chome and shares of different building types within a given chome. Other variables included in our analysis include dummy variables to capture whether a plant belongs to a multi-plant firm (*MULTI*), and whether or not the plant is in a designated reconstruction priority zone (*RECON*) where urban reconstruction costs were heavily subsidized and planning schemes were implemented to improve urban living (new roads, parks etc.). Other standard controls that we include are the age of the plant (*AGE*) and the average wage within a plant (*WAGE*) as a proxy for the average skill level of the workforce. Finally, we include a measure of total factor productivity (*TFP*) based on the approach outlined in Cui *et al.* (2012 and 2015) who construct a measure of TFP that does not require a direct measure of capital. The online appendix outlines how we estimate TFP. We also capture productivity using the more traditional value added per worker (*labprod*).

Finally, we also control for the effect of possible agglomeration forces (*ClusterPlants*) that will capture whether plants choose to geographically cluster in order to benefit from positive externalities of being near firms in the same industry (e.g. supply of workers with similar skills or

[15] We assumed that the age of building was the medium value between categorical thresholds. For example, buildings constructed between 1955 and 1965 were assumed to be 44 years old in 1994.

established markets selling certain goods). Hence, we include the variable *ClusterPlants,* which measures the number of plants within the same two-digit industry and same chome.[16]

3.4 Data descriptives

We now provide a brief description of our data. In Table 1 we provide a summary of the industrial structure in Kobe as well as estimates of the average plant-level damage for each industry using the previously defined colors Pink (fire), Red (severe) and Orange (moderate), Yellow (low). Table 1 shows that the rubber industry had the largest number of plants in Kobe, reflecting the fact that this industry includes the non-leather shoe firms. The rubber industry also experienced a high level of moderate to severe damage (46.1%) with only the non-ferrous metals industry experiencing greater damage. We are reassured that these summary statistics match the anecdotal evidence and Kobe City statistics.

[Table 1 about here]

In figures 5, 6, 7 and 8 we present descriptive evidence of changes in the number of plants, total employment, the exit rate of plants and the number of new plant births over our time period.[17] The immediate observation from figure 5 is that the number of plants in Kobe fell from over 4300 to around 2100 by 2007, coupled with a steadily declining workforce which fell from over 100,000 to a little over 70,000 by 2007 (figure 6). In figure 7 we can observe the large increase in the exit rate in the year after the earthquake in 1995 where it reached close to 14% in 1995 before remaining relatively stable at below 10% for the rest of the sample period. Note that the 1995 exit rate in figure 7 is actually the average exit rate for 1994 and 1995 since missing data for 1994 means we cannot accurately identify whether a firm that was present in our dataset in 1993 but not in 1995 actually died in 1994 or 1995. Taking the average is likely to provide a conservative estimate of the real 1995 exit rate as we are giving equal weight to exit rates in 1994 and 1995 when, in reality, the latter was likely to have been larger. Finally, Figure 8 provides the number of new plant births in Kobe between 1993 and 2007. As can be seen, relative to 1993 plant births fell following the earthquake but rose steadily until 1998 only to fall again. The same pattern then appears to be repeated for the remaining years of the sample.

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[16] We also define clusters by (1) the number of other plants within the same industry as plant *i* within the same or neighboring chomes (*ClusterPlantsNb*), (2) the level of employment within the same industry as plant *i* within the same or neighboring chomes (*ClusterEmp*), and (3) the level of employment within the same industry and same chome (*ClusterEmpNb*). See Collins (2008) for a discussion of the post-earthquake biomedical cluster in Kobe.

[17] Since births are defined as a the new appearance of a plant in our sample it is not possible to identify a new plant in the first year of our sample. Similarly, deaths are identified by a firm disappearing from the sample. Figures 7 and 8 therefore provide deaths and births, respectively, for 1993-2007.

[Figures 5, 6, 7 and 8 about here]

Table 2 provides the change in labor productivity over the sample period for new entrants, plants that died during the sample period and for continuing plants.[18] As can be seen, productivity growth of new entrants is higher than for dying or continuing plants. It is notable that plants that subsequently died during the sample period and continuing plants all, on average, experienced a reduction in productivity over our sample period.

[Table 2 about here]

Appendix Tables A1 and A2 provide a description of our variables and summary statistics. Table A2 shows for example that the average age of a plant is just over 18 years old, and 14% of plants are part of a multi-plant firm. Note that 40% of plants were designated as being located in one of the special reconstruction zones defined earlier. Finally, most firms were built between 1966 and 1975 and are fairly equally distributed between brick, wood, steel and reinforced concrete.

4. Decomposition Analysis

Given our interest in the impact of the Kobe earthquake on productivity, our first empirical exercise decomposes aggregate changes in average sectoral labor productivity (valued added per worker) for 26 sectors in Kobe into changes in productivity due to plants exiting, plants entering and plants that survive the earthquake and continue to operate. Following Baily *et al.* (1992) we use sectoral weights to obtain the overall average for sales for the start and end year of each data point. Although there is inter-annual variability, there is a clear rising trend in labor productivity in the first seven years following the earthquake. The rise in productivity between the first year of our sample and the end year (1992-2007) is 14.8 per cent.

In order to gauge what role earthquake damage might have played in the observed rise in labor productivity in Kobe over our sample period we employ a simple accounting exercise developed by Foster *et al.* (2006). More specifically, Foster *et al.* (2006) decompose the change in sectoral productivity into the component due to the performance of continuing plants (C), that due to entering plants (N), and the component resulting from the exit of plants (X). We expand this decomposition to further disentangle the separate roles of plants affected (d=1) and those little affected or not affected by earthquake damage:

[18] For plants that died during our sample period the productivity change is calculated between 1993 and the final year of the plant's existence.

$$\Delta LP_{it} =$$

$$- \sum_{e \in X; d=1} s_{et-1}\left(LP_{et-1} - LP_{it-1}\right) \; - \sum_{e \in X; d=0} s_{et-1}\left(LP_{et-1} - LP_{it-1}\right) \qquad \text{[EXITS]}$$

$$\sum_{e \in C; d=1} s_{et-1}\Delta LP_{et} \; + \sum_{e \in C; d=0} s_{et-1}\Delta LP_{et} \qquad \text{[CONTINUING]}$$

$$+ \sum_{e \in C; d=1} \left(LP_{et-1} - LP_{it-1}\right)\Delta s_{et} \; + \sum_{e \in C; d=0} \left(LP_{et-1} - LP_{it-1}\right)\Delta s_{et} \qquad \text{[CONTINUING]}$$

$$+ \sum_{e \in C; d=1} \Delta LP_{et}\Delta s_{et} \; + \sum_{e \in C; d=0} \Delta LP_{et}\Delta s_{et} \qquad \text{[CONTINUING]}$$

$$+ \sum_{e \in N; d=1} s_{et}\left(LP_{et} - LP_{it-1}\right) \; + \sum_{e \in N; d=0} s_{et}\left(LP_{et} - LP_{it-1}\right) \qquad \text{[ENTRANTS]}$$

[2]

where LP denotes labor productivity, *s* is the employment share of the plant group in question, and *i*, *e*, and *t* subscripts refer to industry, establishment and time, respectively. The second, third and fourth terms (CONTINUING) are a combination of three different effects. First, a "within" effect that captures the changes in productivity within continuing establishments', i.e., those that were present in both 1992 and 2007, weighted by their initial share of sectoral employment. Second, a "between" effect that represents the component due to changing shares of continuing establishments, weighted by deviations from the initial industry level average productivity and finally a third "cross" term. The "cross" term is positive if on average continuing establishments that have had a positive productivity change, increased employment and/or that those with negative productive changes are likely to have decreased their employment levels. In contrast, if the "cross" term is negative then on average those firms that increased their employment share experienced a fall in productivity and those that saw a reduction in employment experienced an increase in productivity. In our analysis we sum the within, between and cross effects together to get an overall picture for continuing firms.

The first and final terms in equation (2) represent the role played by exits (EXITS) and entrants (ENTRANTS) in sectoral labor productivity changes, respectively. In terms of implementing equation (2) in our context there are a number of points to note. First, we look at changes between the first year of our sample, 1992, and 2007 at the end of our sample period. We are therefore implicitly missing any plants that enter after the earthquake but exit before the end point. Second, the definition of damaged (where d=1), differs between plants that continue or exit and plant births. In the former we simply use building damage. In the latter, those plants that enter are classified according to the average level of building damage within the chome in which they choose to locate.

As a starting point, to classify plants into a damage category we use a building damage level of 20% (i.e. color code yellow) and an equivalent chome damage level cut-off. In Table 3, column (1) presents the results for each decomposition term, as a percentage of average sectoral labor productivity growth. The largest contributors to the overall growth in labor productivity are the entrants (ENTRANTS), both those that locate in damaged chomes and those that locate in undamaged chomes. This is consistent with the strong positive change in labor productivity for new entrants reported in Table 2. In contrast, for continuing plants, we find that while both damaged and undamaged surviving plants have tended to reduce sectoral productivity, the overall negative effect is substantially larger for undamaged plants (-0.49) than for their damaged counterparts (-0.23). In other words, if damaged plants survive they tend to be relatively more productive than those that are not directly damaged. This result is an indication that there may have been an element of a "build back better" effect which raises future productivity.

[Table 3 about here]

When we compare the relative contribution to sectoral productivity we find that there is a noticeably larger contribution from the exit of damaged rather than undamaged plants (0.13 versus 0.09). In contrast, for new entrants, although both positive, those plants that choose to locate in damaged chomes contribute substantially less to the overall rise in sectoral labor productivity than those that choose to locate in undamaged areas. One possible explanation is that subsidies encourage plants to start up in damaged areas and in new sectors. In contrast, the productivity contribution of plant closures, as can be seen from the shares of the EXITS component, was somewhat larger for damaged plants. This is again suggestive of a cleansing effect where earthquake damage results in the closure of the most inefficient plants thereby increasing the average productivity of survivors. [19]

[19] Fukao and Kwon (2006) undertake a decomposition of total factor productivity growth in manufacturing for Japan as a whole over the period 1994-2001. They find that the very slow (0.31%) TFP growth over this period decomposes into a large entrant effect (0.16), consistent with our analysis for 1992-2007. However, in contrast to our analysis they find that continuing plants made a positive 0.22 contribution to TFP growth while exiters made a negative 0.07 contribution. We are very reluctant to infer that these differences may be due to the effect of the earthquake and instead believe that they are likely to be driven by the idiosyncratic nature of the Kobe economy and its reliance on traditional, declining industry together with the differences in our study and that of Fukao and Kwon (2006) referred to above.

In columns (2) and (3) of Table 3 we use different cut-off damage levels to classify plants. First, we increase the minimum damage both at the plant level for continuing and exiting plants and at the chome level for entrants from 20% to 50%. We also reclassify plants as damaged only if their building was completely destroyed, but since there were very few chomes completely destroyed we used the corresponding minimum damage level of 75%. The components that determine the trend in labor productivity are similar. Comparing damaged to undamaged plants shows that the within components remain relatively unchanged both qualitatively and quantitatively. The main exception, however, is in terms of the within productivity component of continuing plants. In particular, as one increases the threshold damage level the negative contribution of surviving damaged plants falls considerably, while that of undamaged plants rises. This suggests that plants in less damaged buildings suffered greater productivity losses, perhaps because they did not have to do as much capital and infrastructure updating as those that were located in buildings that were severely damaged. Likewise, damaged plants were able to access funds for investment at a low cost which put undamaged plants at a potential competitive disadvantage.

5. Plant Exits

In the previous section the suggestion is that the least productive plants exit through a cleansing effect that increased the average productivity of survivors. To investigate further we use a Cox proportional hazard modelling approach (Cox, 1972) to quantify the effect of earthquake damage on plant survival in the short term but also over subsequent years. Of course some, or even possibly all, of any difference in survival rates between damaged and non-damaged plants could feasibly be due to differences in other characteristics. To disentangle the quantitative effect of earthquake damage more precisely we thus estimate a Cox proportional hazards model. We denote the hazard rate of plant i by λ_{it} which represents the probability that the plant exits in interval t to $t+1$, conditional upon having survived until period t given by:

$$\lambda_{it} = \lambda_0(t) exp(\boldsymbol{Z}\beta) \qquad [3]$$

where $\lambda_0(t)$ is the baseline hazard, t is the analysis time, $\boldsymbol{Z}$ is a vector of explanatory variables, and β are our parameters to be estimated. A key feature of the Cox model is that the baseline hazard is given no particular parameterization and can be left un-estimated. However, the proportional hazards assumption requires that each plant's hazard is a constant multiplicative replica of another plant's hazard.[20] The effect of the function $exp\ (Z\beta)$ in equation (3) is to scale the

[20] Equation (3) can be modified to incorporate unobservable heterogeneity across plants or 'frailty' as it is often known. If not controlled for, frailty can reduce the magnitude of estimated coefficients (or hazard ratios) and can

baseline hazard function that is common to all units up or down. The implication is that the effect of covariates in proportional hazards models is assumed to be fixed over time. We test this assumption by analysing the residuals following Grambsch and Therneau (1994).[21]

Apart from our damage proxies, vector $\boldsymbol{Z}$ contains other variables likely to influence plant survival described in the previous section. In addition, the previous literature has established that a number of factors influence the survival of plants. For example, Dunne *et al.* (1988, 1989) establish the important role played by plant age and size and most subsequent papers confirm these findings (for example Bernard *et al.* 2006, Haltiwanger *et al.* 2013 and Fort *et al.* 2013). Bernard and Jensen (2007) find that multi-plant and multinational firms in the US have lower survival rates, while Gorg Görg and Strobl (2003) find that Irish plants that are majority foreign owned also have lower survival rates. Disney *et al.* (2003) in a study of UK manufacturing plants find that those that belong to a larger group are less likely to fail. Bernard *et al.* (2006), along with several others (e.g. Bernard and Jensen 2007), also emphasises the positive role played by productivity which is shown to increase survival rates. Neffke *et al.* (2012) examine the effect of agglomeration economies on plant survival and find that results differ depending on the type and age of the plant. Finally, in a related study, Falck (2007) finds that a new establishment has a greater survival probability the greater the number of new businesses in the same region and same industry.

Given the literature discussed above we include the following control variables. To capture firm size we include dummy variables for three of the four quartiles of total employment (the first quartile dummy is omitted). Including a continuous measure of size does not change the results qualitatively or quantitatively. We also include a measure of the average wage within a plant (*WAGE*) as a proxy for the skill level of the workforce. Finally, we include a measure of TFP on the basis that productive plants are more likely to survive than less productive plants. We also examine whether being part of a multi-plant firm helps survival (*MULTI*) and whether a plant being originally located in a reconstruction zone (*RECON*) influences the probability of survival. Given that the close proximity to other plants in the same industry may also impact on survival either positively or negatively, we also include our agglomeration measure (*CLUSTER*). While

change the interpretation of hazard ratios which, in the presence of frailty, would decline over time. We therefore test a specification in which plant-specific frailty is included and which provides an estimate of θ, the frailty variance component. In all estimations θ was not statistically significant and was very close to zero. These results suggest that frailty is neither economically nor statistically significant in our models. As a result, the estimated hazard ratios with and without frailty are identical (to at least 4 decimal places). Hence, we exclude frailty from our main results although our sensitivity analysis does include a parametric model which incorporates plant-specific frailty.

[21] More specifically we undertake a test of nonzero slope in a generalized linear regression of the scaled Schoenfeld (1982) residuals on functions of time.

older plants are more likely to survive than younger plants we cannot include a direct measure of plant age in a Cox proportional hazards model as it would be collinear with the baseline hazard function. Therefore, we include plant age in 1995 (*AGE*) as a time invariant measure of plant age.

We also include 162 industry dummies, year dummies, and dummies to capture the possible influence of being located in different wards within Kobe city. Finally, we include five different dummies for the average age of the buildings within each plant's chome and the share of building construction types within each chome (wooden, reinforced concrete, steel or brick). These additional controls also demonstrate the richness of the data and how the inclusion of these dummies helps to mitigate a number of the endogeneity concerns present when more aggregate damage proxies are used.

In our dataset we identify plant death if a plant was present in one or more years and then disappears from the dataset.[22] Since we are missing data for 1994, this means that plants present in our data in 1993 that were not present in 1995 could have died in either 1994 (i.e. pre-quake) or in 1995 (post-quake). In our survival analysis we therefore omit the pre-quake period and hence the earliest plant deaths that we can capture are plants that were present in our data in 1995 but not in 1996. We are therefore trying to ascertain how those plants that survived the immediate effects of the earthquake were subsequently affected by any earthquake damage incurred.

Before proceeding to our analysis it is important to state the identifying assumption behind our econometric specifications. Essentially, an unbiased estimate of the impact of our damage variables hinges on the assumption that after controlling for plant-level characteristics prior to the earthquake and the building types within chomes, any differences in damages experienced are not correlated with other unobservable determinants of plant performance. A concern might be that some plants chose their location so as to reduce their exposure to seismic risk and that these plants are also characterized by other factors that would influence their survival regardless of whether an earthquake had occurred or not. As noted earlier, we are confident that the earthquake was unexpected, so that such anticipatory behaviour would have been unlikely. Nevertheless, even if this was not the case it could be by pure chance that those plants that were anyway more likely to survive happened to be located in buildings that were more or less earthquake proof or in areas with overall less or more damage. However, we believe that the number of plant-level explanatory variables that the census provides us with makes such a

[22] This is appropriate since our dataset is comprehensive and includes all manufacturing plants in Kobe.

violation of the assumption unlikely. One aspect that we do not capture are the characteristics of the actual plant's building. Instead, as described above, we have chome level measures of building types, namely the age and construction material type. Reassuringly though, chomes tend to be fairly homogenous in their building type. For example, in 50% of all chomes the dominant building type constituted over 75% of all buildings with a standard deviation of 0.15%. Similarly, while the average age of buildings for those built after 1945 was approximately 33 years, the standard deviation within chomes was only eight years. In contrast, there is clearly more within-chome heterogeneity in terms of damage type of buildings. For example, the most dominant building type constituted less (69%) than the distribution of building types and almost double the standard deviation (0.28%).

Nevertheless, to ensure that plant characteristics are not influencing the earthquake damage incurred by plants we estimate a cross-sectional regression expressing plant-level earthquake damage as a function of pre-earthquake plant-level characteristics age, size, wage, TFP and our cluster variable (the model also contains controls for industry, age of buildings in chome and type of buildings in chome.) None of these plant-level characteristics are statistically significant determinants of plant-level earthquake damage (even at 10% significance levels).[23]

We now turn to our results. Our main survival analysis results are presented in Table 4. To help with the interpretation of the coefficients recall that a hazard ratio on a continuous variable (e.g. WAGE) of, for example, 1.1, is interpreted as saying that a 1 unit change in that variable increases the hazard of plant exit by 10%. Similarly, if the hazard ratio is 0.9 then a 1 unit increase in the variable reduces the hazard by 10%.[24]

[Table 4 about here]

We begin in Columns (1) and (2) with measures of earthquake damage that have previously been used as proxies for damage but do not take into account the possibility of heterogeneity in damage to plants within relatively small geographical areas. The variables are the distance to the epicentre and local peak ground acceleration. In terms of distance to the epicentre we find, surprisingly, a hazard ratio that is significantly greater than one, suggesting that within the City of Kobe the further away from the epicentre the greater the chance of plant closure. Although seemingly counter-intuitive, the result is explained by the actual pattern of the earthquake

[23] Results are provided in Table A of the online appendix.

[24] As previously discussed, for each model we test whether the effect of covariates is constant over time. For the models in Table 4 we find that this assumption is inappropriate for the variables *WAGE* and *RECON*. We therefore interact these variables with a linear time trend, thereby allowing the hazard ratio to vary over time. The inclusion of these interactions does not affect the sign and significance of these or any other variables.

damage which was concentrated in a narrow strip of land stretching away from the epicentre which we previously discusssed in Section 2. Our result highlights the potential problems with using simple distance to the epicentre as a proxy for plant damage. Model (2) includes our measure of local peak ground acceleration, *SHAKE* (illustrated in figures 3 and 4). Our results show that *SHAKE* is not statistically significant. One explanation for this insignificance is again the level of heterogeneity shown in figure 4 and discussed in Section 3.2.

A third measure of damage that has been previously used in the literature is a regional or local spatial measure of damage. Hence, in model (3) we include the average building damage at the chome-level (*ChomeDAM*). The estimated coefficient is also statistically insignificant. Figure 4 shows that giving each building within a chome a damage index based on our color classification will induce considerable measurement error. This again shows the importance of local damage heterogeneity.

We now turn to our plant specific damage variables. Our building-level damage variable (*PlantDAM*) is included in model (4). This variable is statistically significant with a hazard ratio of 1.61 suggesting that a one unit increase in damage (representing a 100% damaged building) leads to a 61% increase in the probability of permanent plant closure. In column (5) we include a smoothed plant damage variable (*SMOOTH*) that takes into account damage to plants nearby as a robustness check. Reassuringly, the results are quantitatively similar to our *PlantDam* variable.[25] In model (6) in addition to our plant damage variable we also control for the average level of *ChomeDAM* but this has little effect on the *PlantDAM* variable and is, in itself insignificant. Note, however, that including these damage variables in this manner allows only for a permanent impact of earthquake damage on plant survival.

More realistically, one might expect the impact of earthquake damage on the chance of survival to decline over time. In model (7) we interact the chome-level damage and plant-level damage variables with *Time*, a variable capturing the number of years that have passed since the earthquake. We now find that *ChomeDAM* is statistically significant, with a hazard ratio indicating that greater chome level damage increases the probability of plant exit. The magnitude of the hazard ratio on *ChomeDAM* is now greater than that on *PlantDAM* although the *Time* interaction terms reveal that the negative effect of these factors on survival diminishes over time and declines more rapidly for *ChomeDAM*.

[25] We would like to thank an anonymous referee for the suggestion. The SMOOTH variable is calculated as the average damage for all buildings within 100m of the plant (excluding own plant damage). The results give us confidence that our plant damage variable does not suffer from the endogeneity concerns discussed in Section 3.4.

Turning to our other control variables the coefficients are remarkably stable across all specifications. More specifically, we find that older plants and higher wage paying plants are less likely to exit but the effect is small. Our size variables all have hazard ratios below one indicating that larger plants are less likely to exit relative to the smallest plants which form the omitted category. Plants that are part of a multi-plant firm appear to be more likely to close, a finding consistent with Bernard and Jensen's (2007) and Craioveanu and Terrell (2016)'s finding for US plants and explained by firms moving production to other plants within the firm instead of repairing the damaged plant and resuming production. Our *TFP* variable has a hazard ratio of less than 1 suggesting that more productive firms are more likely to survive (in unreported results our simple labor productivity variable gives a similar result). Finally, our measure of the degree of plant agglomeration (*ClusterPlants*) which measures the number of plants from the same 2-digit industry in a given chome has a hazard ratio greater than 1. This suggests that plants that belong to a cluster are more likely to exit and may reflect the increased competition associated with a heavy spatial concentration of plants from the same industry and more importantly a breakdown of agglomeration economies that had previously allowed the cluster to thrive despite, for example, increased competition from China.[26] Our variable to capture whether a plant was located in one of the eight special reconstruction zones is not significant.

In Table 5 we further investigate our primary finding that plant damage significantly impacts the probability of plant survival. For reasons of space, we report only results for our damage variables, although each model includes all of the plant characteristics reported in Table 4 together with our industry, year, and ward dummies, and the age and type of buildings in each chome. In model (1) we replace our Cox proportional hazard model with a Probit model to estimate the probability of plant exit. *PlantDAM* is again shown to be a positive and statistically significant determinant of plant exit although its interaction term with years since the earthquake is not significant while *ChomeDAM* and its interaction term with *Time* both remain significant. Model (2) is a parametric survival model provided for comparison and incorporates plant-specific frailty, as previously discussed.[27] *PlantDAM* and its interaction with time are statistically significant, as are *ChomeDAM* and its interaction with time. We also report θ, the frailty variance component which is insignificant and close to zero indicating that frailty has almost no effect within this model.

[26] We also alternatively used our other clustering proxies described in the data section. These results are reported in the online Appendix (Table B) and are very similar in terms of sign and significance.
[27] The parametric model was estimating using the exponential distribution. Of all the available distributions, the exponential distribution provided the lowest Akaike Information Criterion. Frailty itself is modelled using a gamma distribution.

Model 3 replaces our *PlantDAM* variable in the Cox proportional hazard model with individual dummy variables for pink, red, orange, and yellow levels of damage, where green (no damage) is the omitted category. We also include the *ChomeDAM* variable but exclude time interactions so that we are able to see how the hazard shifts across categories. The results suggest that it is pink and red damage that is driving our results. However, when we include chome damage and time interactions in model (4) we find that all four dummy variables, together with their time interactions, are statistically significant. As one might have expected, the hazard ratios for pink and red plant damage are larger than those for orange and yellow damage. Model 5 includes individual variables capturing the chome-level share of each building damage type together with their interactions with time. The proportion of red, orange and yellow damaged buildings in a chome is found to significantly influence plant exit. The magnitude of the hazard ratios on the chome damage variables are broadly similar to those on the plant damage variables and, again, the hazard ratios decline over time.

[Table 5 about here]

In almost all cases we find that not only are our plant and chome level damages variables significant but so are their time interaction terms, where the hazard ratios suggest a negative impact that declines over time. In Figure 9 we plot the implied plant specific damage hazard ratios over time for the final model in our main results table (model 7 in Table 4), and, separately, for the individual levels of damage (model 5 in Table 5). Observe that the hazard ratio remains above one until at least 2002 for all but the most minor level of damage (yellow). This suggests that plants that were damaged by the earthquake were more likely to exit than undamaged plants for up to seven years after the earthquake. For plants that experienced fire (pink) damage, the effect lasted for up to nine years. Plants that experienced the least severe yellow level of damage were more likely to exit than undamaged plants for up to five years after the earthquake.[28] However, figure 9 also shows that the greatest exit rate was immeditately following the earthquake (consistent with figure 7).

[Figure 9 about here]

For reasons of space we do not plot the hazard ratios associated with chome level damages over time. However, the results from model 7 in Table 4 and models 2 and 5 in Table 5 indicate that the effects of *ChomeDAM* are of a similar, or even greater, magnitude than the effects of *PlantDAM* but are shorter lasting. More specifically, within four years plants that were located in

[28] Hazard ratios from models 2 and 4 in Table 5 are plotted in Figure C in the online Appendix. In each case the duration of the earthquake impact from these models is very similar to those presented in Figure 9.

a chome that suffered complete building damage were no more likely to exit than plants that did not experience any damage.

To assess the sensitivity of our results to the construction of our single index *PlantDAM* variable, which uses the median value of damage within each damage category, we randomised this factor for each damage category. Firstly, we assigned the same randomly chosen damage value to all plants within a damage category. Secondly, we randomly assigned a different value of damage to each plant within a category. For both procedures the randomly chosen value was bounded by the upper and lower damage values within each category.[29] This exercise was conducted 500 times for each case and then our specification of model (7) in Table 4 re-estimated. Figures D and E in the online appendix depict the distribution of the estimated hazard ratio derived from the coefficients on the plant specific damage variable and its interaction with time. More specifically, Figure D provides the mean, 5% level and 95% level of implied hazard ratios over time from the 500 different estimations in which the same randomly chosen damage value is assigned to each plant within a damage category, whereas Figure E provides the counterpart for when a different randomly chosen damage value is assigned to each plant within a damage category. In both exercises, the *PlantDAM* and *PlantDAM*Time* variables were significant in all 500 estimations. The two figures show that the mean hazard ratio is similar in magnitude to those from the 'main Cox' model in Figure 9, although there is more confidence in the estimated effect from the sample where plants' damage values can differ from those of other plants in the same damage category. These results provide some confidence that the results are not sensitive to the manner in which the *PlantDAM* index was constructed.

Finally, we try to throw some light on the nature of the plants most likely to fail as a result of earthquake damage. We do this using the model (7) specification in Table 4 applied to various sub-samples of our data. Specifically, we estimate the model, separately, for the lowest quartile of plants in terms of TFP, labor productivity, size, age and skill-level (measured using average wage). Having estimated hazard ratios for each of these sub-samples we can then compare them with the hazard ratio for the full-sample to see if, for instance, plants in the lowest quartile in terms of TFP have higher hazard ratios than the average plant in the full sample. Table 6 provides the estimated hazard ratios for each sub-sample which, for convenience, can be compared to the hazard ratio for the full sample in column (1). Table 6 also indicates if the hazard ratios for each sub-sample are statistically different to those from the full sample using Likelihood Ratio tests. Compared to the full sample the hazard ratio on *PlantDAM* is greater in

[29] For the chome level damage variable we similarly randomly assigned a value within each category's upper and lower threshold.

magnitude, and statistically different to the hazard ratio for the full sample, for plants that are in the lowest quartile in terms of TFP, labor productivity, size and skill-level. This indicates that unproductive, small, low-skill plants were more likely to immediately fail as a result of earthquake damage than the average plant in the sample. The hazard ratio for the youngest quartile of plants is not statistically different to that from the full sample. The interaction of PlantDAM with time suggests that the effect of earthquake damage on unproductive, small, low-skill plants lasts for a similar length of time to the plants in the full sample.

[Table 6 about here]

6. Continuing Plants

Having examined the effect of earthquake damage on plant survival more generally, we now investigate how such damage may have affected the performance of surviving plants. Note that we limit our sample to those plants that are still operating at the end of our sample period (the results do not change substantially when we include those plants that exited during the period). Our final sample consists of a balanced panel of 835 surviving plants for the period 1992-2007. Starting in 1992 means we have plant data before and after the earthquake. We estimate a fixed effects panel model of the following form:

$$Y_{it} = \alpha_i + \gamma_t + X\delta + \varepsilon_{it} \qquad [4]$$

where Y_{it} denotes the log of labor productivity or TFP, in plant *i*, year *t*, X is a vector of explanatory variables, including our earthquake damage proxies, and α and γ are plant and year fixed effects, respectively. As previously pointed out, our measures of damage *PlantDAM* and *ChomeDAM*, take on a value of zero prior to the earthquake and then, for affected plants, take on a positive value, depending on the damage incurred, from then onwards. For undamaged plants they are consistently zero throughout the period. This sort of modelling is equivalent to a difference-in-difference analysis where the treatment is of a continuous (rather than binary) nature once treatment occurs. [30] Equation (4) is estimated using Driscoll and Kraay (1998) standard errors which are robust to very general forms of cross-sectional and temporal dependence.

Table 7 presents the results for equation (4) where each of our left hand side variables is estimated with and without time interaction terms. The results in columns (2) and (4) show that our plant-damage variable is positive and significant when we include time interaction terms,

[30] This is a standard tool in the econometric assessment of shocks; see for instance Angrist and Pischke (2008).

with the interaction terms being negative. This suggests that the earthquake had a positive effect on plant productivity although this effect falls over time. Hence, model (2) shows that a one unit increase in *PlantDAM* initially increases labor productivity of surviving plants by 1.10%, with this effect falling to zero after eight years. The effect for labor productivity is similar. One explanation is that this is capturing a build-back-better effect if surviving plants replaced earthquake damaged physical capital with newer, more efficient capital. In terms of labor productivity it may be that the least skilled workers left Kobe post-earthquake as they may have had less incentive to see if their jobs at damaged plants would resume following reconstruction. Alternatively, they may simply have been laid off by the plant as a short term cost saving exercise until the plant was repaired at which time new workers were hired. An alternative explanation of why damage increases the productivity of surviving plants is simply that plants that are on an increasing productivity trajectory rebuild and those with declining productivity do not rebuild. For labor productivity *ChomeDAM* has a negative effect with the effect getting smaller over time as expected. Both of our productivity variables were positively influenced by the level of wages and whether or not the plant was within a reconstruction zone and negatively affected by being part of a multi-plant firm.

[Table 7 about here]

7. Plant Entrants

Until now we have concentrated on how the Kobe earthquake affected plants that existed at the time of the earthquake. In our final analysis we consider the effect of earthquake damage on plant births. We undertake this analysis at the chome level and estimate the following regression:

$$Births_{jt} = Z\vartheta + \alpha_j + \gamma_t + \epsilon_{jt} \qquad [5]$$

where α and γ are chome and year fixed effects, respectively, and vector Z contains chome-level earthquake damage as well as road damage, whether or not the chome was part of a reconstruction zone, and the number of plants within the chome in the previous year. Subscripts j and t denote chomes and years, respectively. Equation (5) is estimated using a fixed effects negative binomial approach in order to account for both the count data nature of the dependent variable and for the over-dispersion of the data.[31] Note that our sample period for this analysis begins in 1993 rather than 1992 as 1993 is the first year in which births can be identified. This

[31] We also estimate the probability of plant birth using a fixed effects logit model with the results reported in the online appendix (Table C). In each case the results were similar to those estimated using the fixed effects negative binomial regression.

reflects the fact that births are identified by the presence of a new firm in the sample which was not present in previous years. Note also that this method of identifying new births means births identified in 1995 could actually have occurred in our missing year, 1994. For this reason we omit 1995 from the analysis although the inclusion of this year has no impact on the sign and significance of our results.

Table 8 presents the results of our chome-level estimates of the determinants of plant births. In models (1) and (2) we use the *ChomeDAM* variable with and without time interactions, respectively, while models (3) and (4) separate damages into the different damage categories, again with and without time interactions. We find that *ChomeDAM* deters plant births and that this effect does not statistically change over time as shown in model (2). In model (1), for example, *ChomeDAM* has a coefficient of -0.96 which corresponds to an incidence rate ratio of 0.38, implying that a 100% damaged chome would have only 38% of the births of an undamaged chome. Interestingly, the reconstruction dummy, *RECON*, is negative and significant indicating that being classified as a reconstruction zone reduces plant births. From model (1), reconstruction zones only experienced 26% of the births in non-reconstruction zones. This may relate to the nature of the reconstruction which was often residential and retail. Kobe planners were also keen to ensure that the city did not make the mistakes of the past, for example relying too heavily on wooden buildings. For that reason, reconstruction zones may have been subject to more, rather than less, stringent planning regulations.

The results of models (3) and (4) show that the number of buildings that were fire damaged in a chome (pink) did not influence plant births in a statistically significant manner, but the level of severely damaged buildings (red) increased plant births. The incidence rate ratio for *ChomeDAMRed* in model (3) tells us that a chome in which all buildings experienced 'red' damage would experience 84% more plant births than an undamaged chome. This suggests that the fact that buildings were razed to the ground in the most severely damaged chomes meant new investment and plant births were more likely. In contrast, being moderately damaged reduces plant births, with 'orange' and 'yellow' chomes experiencing only 25% and 47%, respectively, of the births of an undamaged chome. The results help explain the strong effect on productivity of plants entering into undamaged areas from Table 2 as there are many more of them.

[Table 8 about here]

8. Conclusions

In this paper we investigate the impact of the Kobe 1995 earthquake on the birth, life and possibly death of manufacturing plants using a spatially heterogenous measure of plant damage. More specifically, we assemble an exhaustive panel of manufacturing plants spanning the period 1992 to 2007 and construct building-specific and area-specific measures of damage. We are also able to control for average building type and age at the local geographical level to help address various endogeneity concerns. Our decomposition results show that the increase in productivity post-earthquake was driven by the exit of plants and the entry of new plants into undamaged areas. Although continuing plants had an overall negative effect on overall productivity, damaged plants did relatively better over our time period. Our survival analysis results show that plant survival is negatively impacted by plant-level damage and that this effect persists for a number of years. More precisely, damaged plants are more likely to fail than undamaged plants up until 2002 which is seven years after the earthquake. This result is in stark contrast to the more macroeconomic studies where the implied duration was much more short-term. Our results also indicate that damage to local infrastructure affects plant failure, although such effects do not last as long as the effects of plant damage. What is evident is that studies that employ far more aggregated measures of damage using shake maps or broad regional measures of damage are subject to considerable measurement error due to the heterogeneous nature of damage caused by natural disasters, especially earthquakes.

In further analysis we show that compared to the average plants those most likely to cease trading were the relatively unproductive, small, young and low-skill plants. In terms of productivity at least, this suggests that natural disasters may play a cleansing role similar to that performed by recessions (Caballero and Hammour 1994 and Ouyang 2009). While an assessment of the overall impact on welfare of the Kobe earthquake is beyond the remit of this paper, such a cleansing role would partially mitigate some of the other economic losses generated by the earthquake. Examining the productivity performance of plants that survived the earthquake we discover evidence consistent with a build back better behaviour among those plants that survived. More precisely, we find that the productivity of damaged plants increased in the years following the earthquake although this disappeared 8 years after the earthquake.

The policy implications are necessarily nuanced. In one respect, policies that provided subsidised loans to damaged plants may well have helped plants survive in the short term and help maintain employment levels. The downside is that this increased indebtedness and when combined with a sluggish Japanese economy meant that plants continued to exit in the years following the earthquake. Likewise, policies to encourage plants to locate in certain areas and in certain sectors may not have been a cost effective use of funds. However, stronger policy perscriptions are not possible without a more indepth analysis of the financial and non-financial aid provided to plants in the aftermath of the earthquake.

Finally, more generally, our paper provides a number of suggestions for the literature on the economic impact of natural disasters. Natural disasters tend to be localised events and moving beyond the micro-level impact is likely to mask the size and duration of any local impacts. Related to this, it is important to be able to precisely capture the heterogeneous nature of these large negative shocks across space in order to have reasonable confidence in their estimated consequences.

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Figure 1. Manufacturing Output in Kobe and the Rest of Japan Relative to Pre-Earthquake Levels (1993=100)

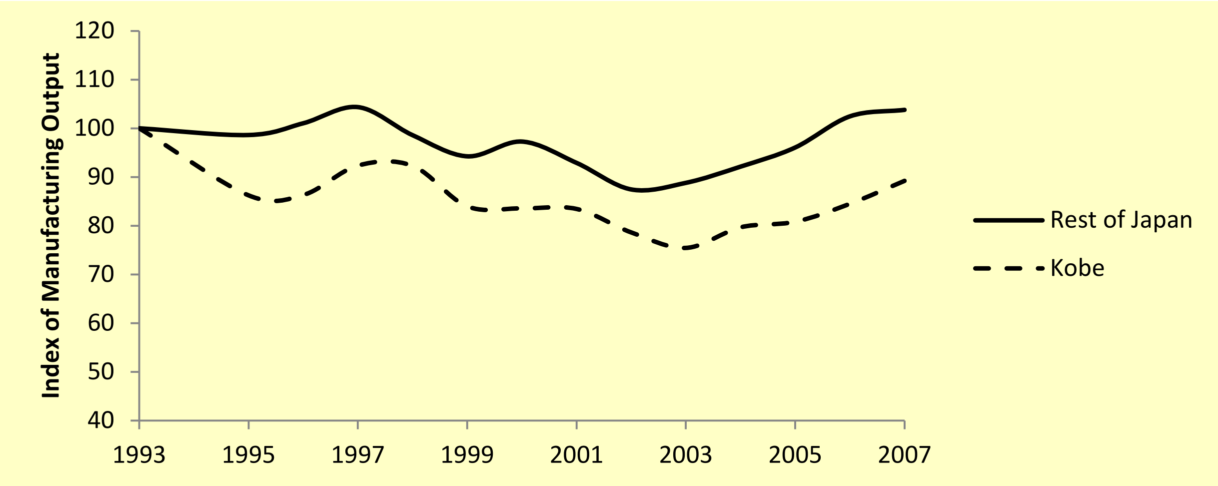
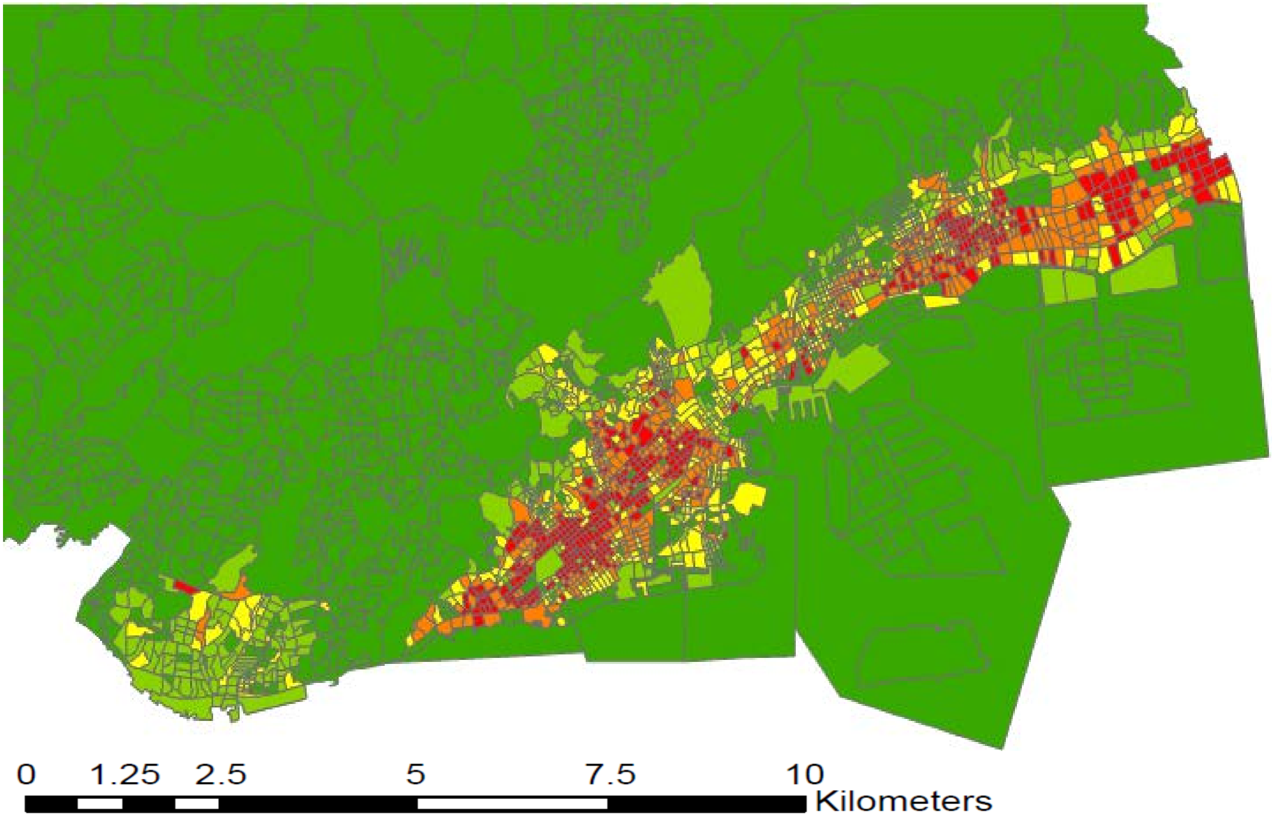


Figure 2: Chome-Level Damages Based on the Average Percentage of Damage to Each Building



Percentage of Building Damage in each Chome:

	0%
	1-3%
	3-20%
	20-50%
	50-100%

Figure 3: A Shake-Map of Kobe City Showing Variation in Peak-Velocity (cm/s).

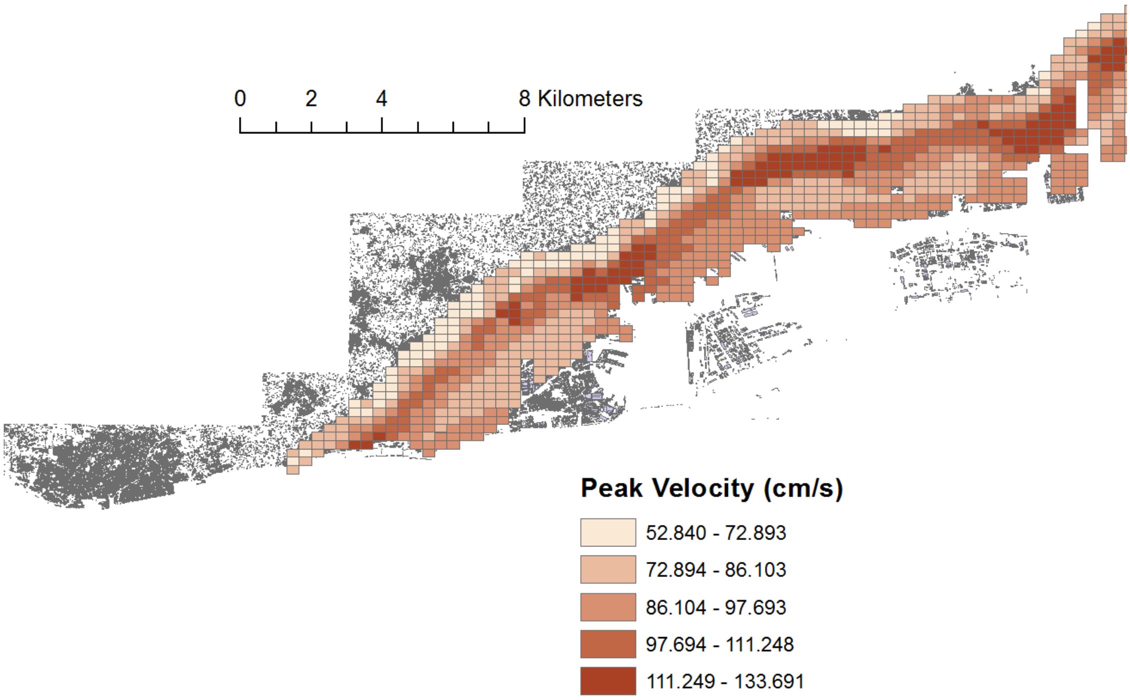


Figure 4: A Shake-Map of a Small Area of Kobe City Showing Building Damage Heterogeneity.

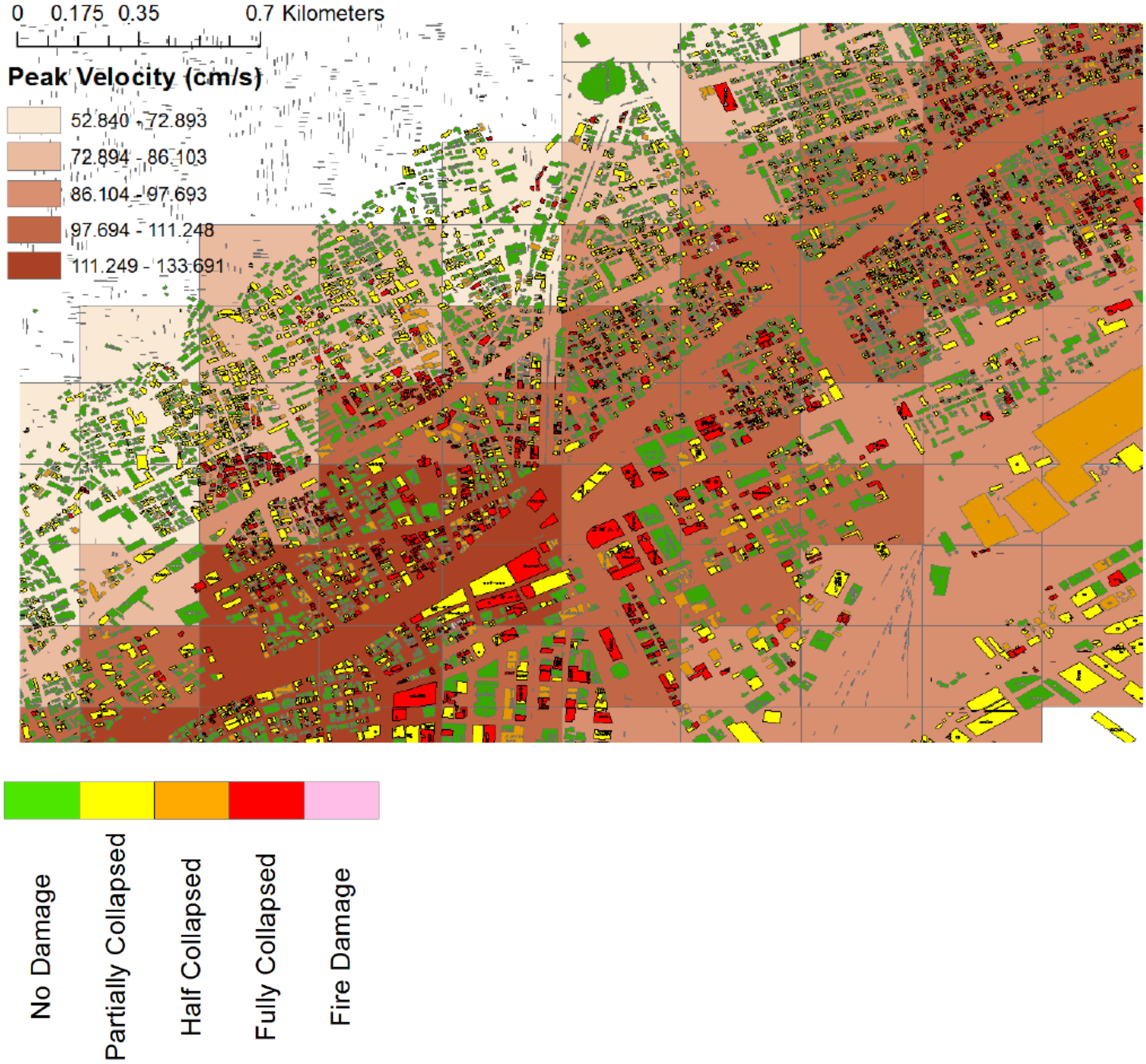


Figure 5. The Number of Manufacturing Plants in Kobe Pre and Post Earthquake

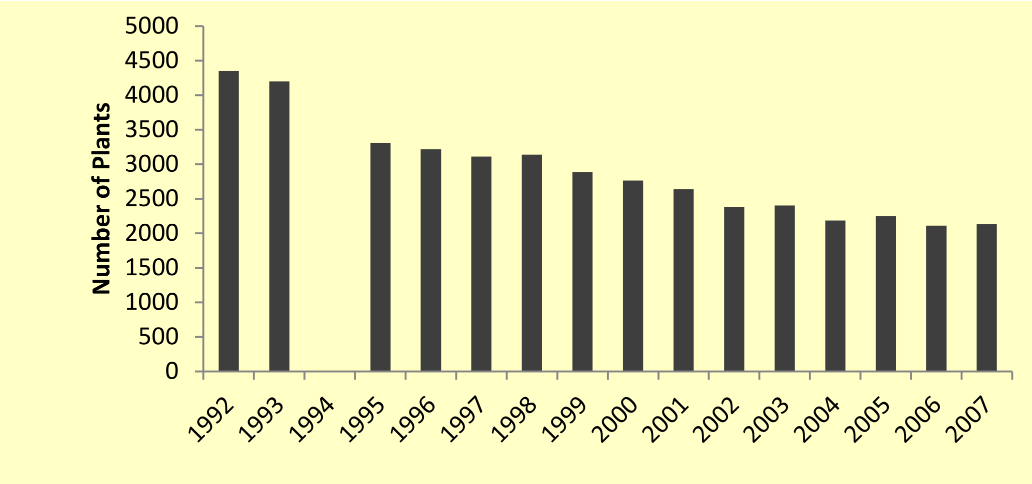


Figure 6. Total Employment in Manufacturing in Kobe Pre and Post Earthquake

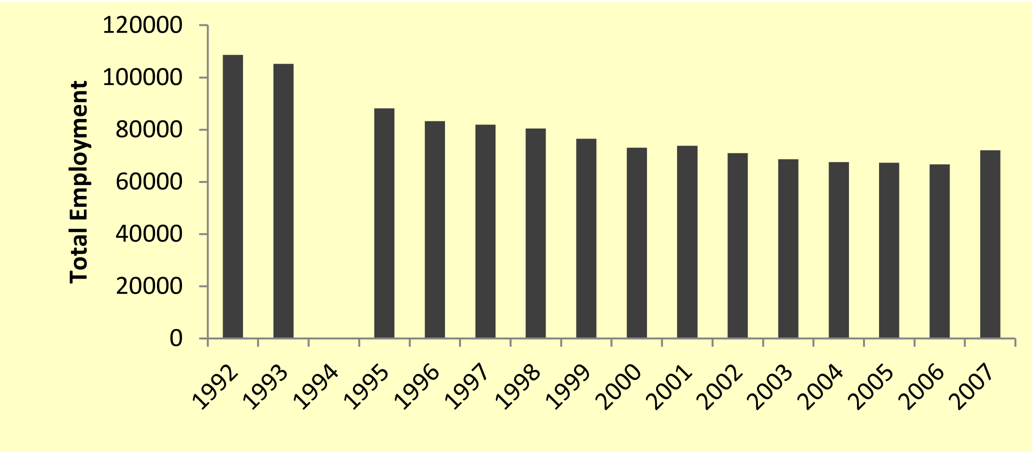
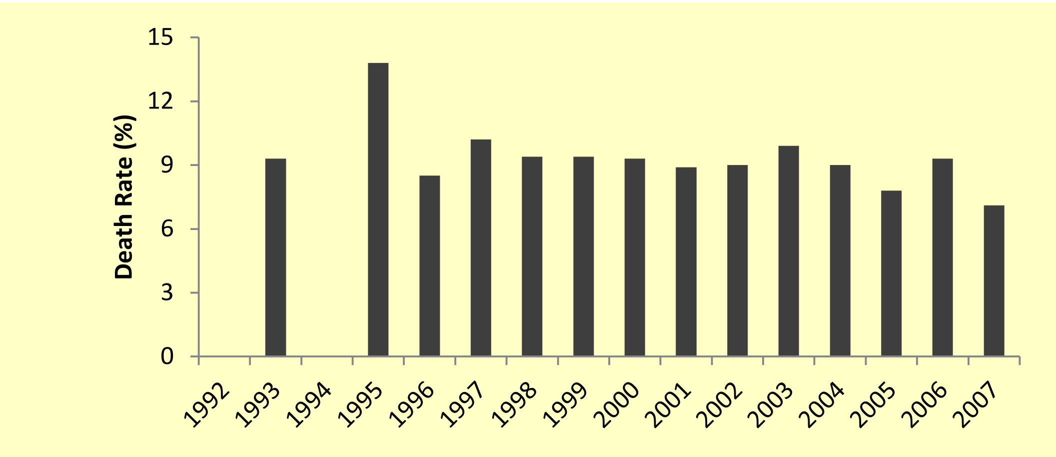
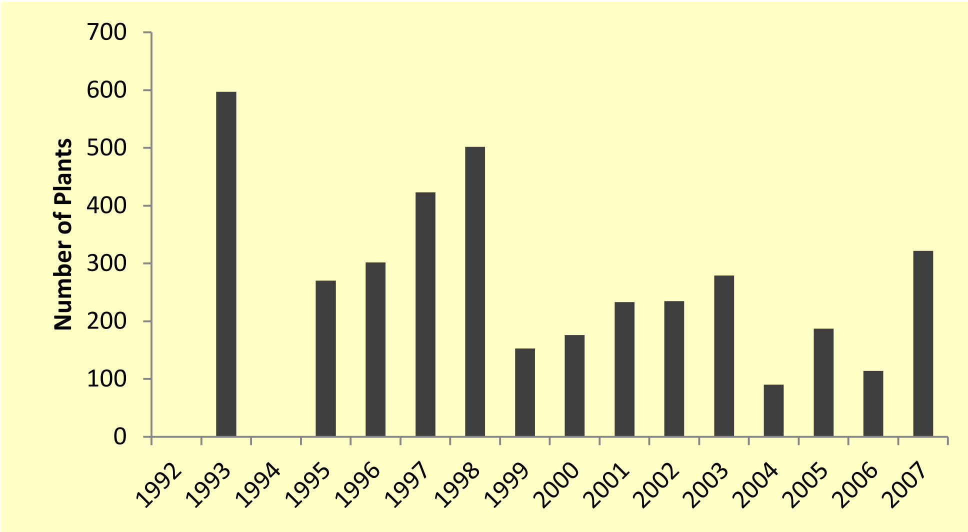


Figure 7. The Exit Rate of Manufacturing Plants in Kobe Pre and Post Earthquake*



* Note that the 1995 exit rate is an average of the 1994 and 1995 exit rates

Figure 8. The Number of New Plant Births in Kobe Pre and Post Earthquake*



* Note that the number of births in 1995 is an average of the births in 1994 and 1995

Figure 9. Plant Damage Hazard Ratios Over Time (from Table 4 (model 7) and Table 5 (model 5))

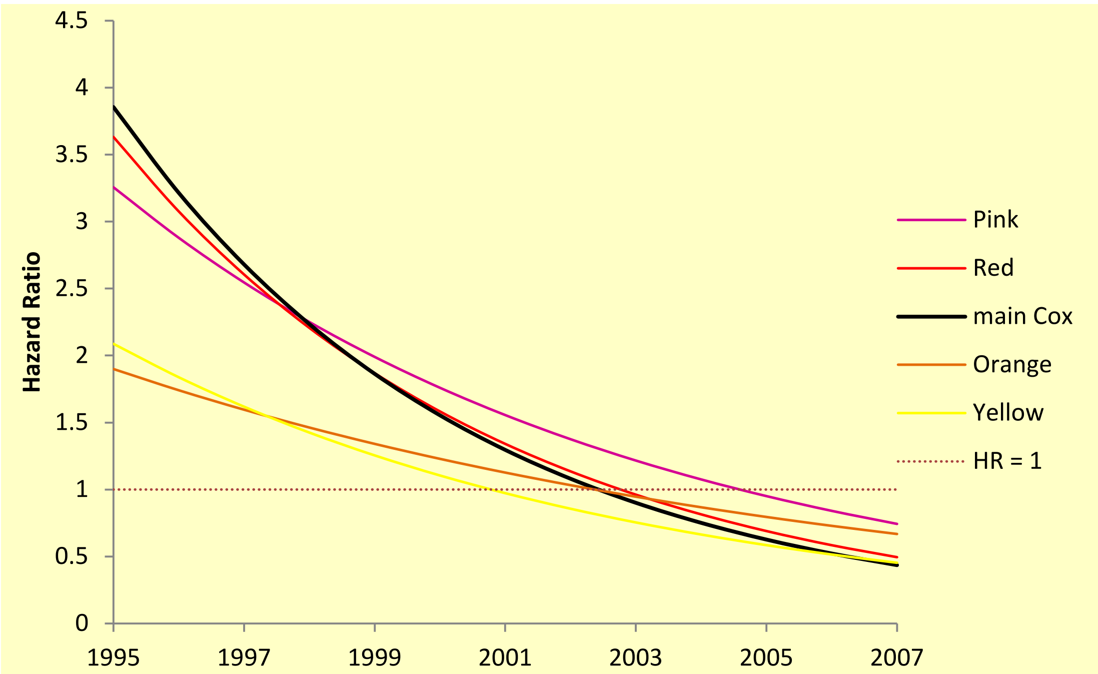


Table 1. Damage by Industry (Ranked by All Damage).[1]

Industry	% of Sample	All Damage	PINK	RED	ORANGE	YELLOW
Non-Ferrous Metals	0.6	85.4	0	15.6	38.5	31.3
Rubber	17	76.2	5.5	24.8	15.8	30.1
Leather and Fur	6.8	74.8	7.5	19.8	16.8	30.7
Information & Communication Machinery	0.4	71.6	0	33.8	8.1	29.7
Pulp, Paper	2.5	71.5	3.4	16.5	21.7	29.9
Furniture	1.4	70.9	0	16.9	23.5	30.5
Industrial Machinery	6	69.1	0.6	14.1	14.9	39.5
Printing	10.5	68.1	0.9	16.5	19.1	31.6
General Machinery	4.6	63.4	1.2	10.4	11.4	40.4
Textiles	4.8	62.4	0	17.4	19.5	25.5
Plastic Products	1.8	60	0	14.9	17.6	27.5
Metal Products	8.6	59.3	1.9	11.2	18.5	27.7
Wood Lumber	1.8	58.3	0	16	17.3	25
Electronic Machinery	3	56.5	3.6	10.1	12.7	30.1
Transport Machinery	5.1	56.2	1.8	8.1	20.7	25.6
Chemicals	1.2	55.6	13.1	19.2	4.6	18.7
Beverages and Tobacco	2.1	55.5	0	9.1	13	33.4
Food	12.3	54.6	1.6	9.4	13.5	30.1
Electronic Devices & Semi-Conductors	0.6	52.1	0	8.3	24	19.8
Oil and Coal Products	0.5	49.4	16.1	0	1.2	32.1
Other Manufacturing	4.6	47.8	0.7	4.9	9.8	32.4
Porcelain and Pottery	1.3	42.9	6.1	18.1	6.1	12.6
Household Machinery	0.8	39.7	0	8.4	6.1	25.2
Iron and Steel	1.3	35.4	0	16.5	2.8	16.1
Newspapers	0.6	23.5	0	7.8	2	13.7

[1] Where 'All Damage' is the sum of pink, red, orange and yellow.

Table 2. Average Change in Labor Productivity 1992-2007 for New, Dying and Continuing Plants.

	Change
New Plants	54.7%
Dying Plants	-39.5%
Continuing Plants	-13.7%

Table 3. Decomposition analysis (Labor Productivity 1992-2007)

Component	DAMAGE (d=1,0)	(1) 20% damage	(2) 50% damage	(3) 75% damage
TOTAL EXITS		**0.22**	**0.21**	**0.21**
EXITS	1 (Damaged)	0.13	0.14	0.11
EXITS	0 (Undamaged)	0.09	0.07	0.10
TOTAL CONTINUING		**-0.72**	**-0.62**	**-0.68**
CONTINUING	1 (Damaged)	-0.23	-0.07	0.01
CONTINUING	0 (Undamaged)	-0.49	-0.55	-0.69
TOTAL ENTRANTS		**1.5**	**1.42**	**1.47**
ENTRANTS	1 (Damaged)	0.58	0.58	0.60
ENTRANTS	0 (Undamaged)	0.92	0.84	0.87

Number of observations = 19,221

Table 4. Main Results of Survival Analysis (Cox proportional hazard)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DISTEPI	1.01***						
	(0.0016)						
SHAKE		1.002					
		(0.0067)					
SMOOTH					1.62***		
					(0.28)		
PlantDAM				1.61***		1.61***	3.83***
				(0.19)		(0.19)	(0.72)
ChomeDAM			1.08			1.01	7.88***
			(0.18)			(0.17)	(2.30)
*PlantDAM*Time*							0.83***
							(0.027)
*ChomeDAM*Time*							0.66***
							(0.031)
AGE	0.9997**	0.995**	0.995**	0.995**	0.997**	0.997**	0.997**
	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
SIZE2	0.50***	0.50***	0.50***	0.49***	0.49***	0.49***	0.52***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.040)
SIZE3	0.39***	0.39***	0.39***	0.40***	0.40***	0.40***	0.41***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)	(0.033)
SIZE4	0.85***	0.85***	0.85***	0.85***	0.85***	0.85***	0.86***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
WAGE	0.998***	0.9997***	0.9997***	0.9997***	0.9997***	0.998***	0.998***
	(0.000046)	(0.000046)	(0.000046)	(0.000047)	(0.000047)	(0.000047)	(0.000048)
TFP	0.89**	0.89**	0.89**	0.90***	0.90**	0.90**	0.91*
	(0.045)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)	(0.047)
MULTI	1.44***	1.44***	1.44***	1.43***	1.43***	1.43***	1.42***
	(0.15)	(0.17)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
RECON	0.9993	1.0025	0.9998	0.995	0.9997	0.996	0.99
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ClusterPlants	1.02**	1.03**	1.02**	1.03***	1.03**	1.03**	1.03**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	16,658	16,658	16,658	16,658	16,658	16,658	16,658
Wald	308594***	318471***	304152***	338214***	311356***	323214***	294578***

Each model contains controls for 3-digit industry, year, ward, age of buildings in a chome and type of buildings in a chome
Standard errors are in parentheses and ***, **, * denote hazard ratios that are significantly different from 1 at 99%, 95% and 90% confidence levels, respectively

Table 5. Survival Analysis Sensitivity Results

	1	2	3	4	5
PlantDAM	0.19**	1.83***			
	(0.09)	(0.32)			
*PlantDAM*Time*	-0.019	0.93**			
	(0.016)	(0.028)			
PlantDAMpink			1.50**	3.05***	3.26***
			(0.26)	(0.96)	(1.13)
PlantDAMred			1.36**	3.98***	3.63***
			(0.13)	(0.72)	(0.73)
PlantDAMorange			1.11	2.41***	1.90***
			(0.10)	(0.48)	(0.38)
PlantDAMyellow			0.94	2.33***	2.09***
			(0.075)	(0.42)	(0.37)
*PlantDAMpink*Time*				0.90**	0.88**
				(0.048)	(0.047)
*PlantDAMred*Time*				0.84***	0.85***
				(0.023)	(0.024)
*PlantDAMorange*Time*				0.89***	0.92***
				(0.025)	(0.025)
*PlantDAMyellow*Time*				0.87***	0.88***
				(0.021)	(0.02)
ChomeDAMPink					1.95
					(0.78)
ChomeDAMRed					2.36***
					(0.75)
ChomeDAMOrange					3.56***
					(1.28)
ChomeDAMYellow					2.83***
					(0.91)
*ChomeDAMPink*Time*					0.86**
					(0.047)
*ChomeDAMRed*Time*					0.81***
					(0.037)
*ChomeDAMOrange*Time*					0.83***
					(0.043)
*ChomeDAMYellow*Time*					0.80***
					(0.036)
ChomeDAM	0.27**	2.55***	1.01	7.95***	
	(0.11)	(0.56)	(0.17)	(2.51)	
*ChomeDAM*Time*	-0.057***	0.82***		0.66***	
	(0.015)	(0.025)		(0.031)	
θ		1.01e-7			
(p value)		(0.47)			
Observations	16,658	16,658	16,658	16,658	16,658

In addition to the firm control variables contained in Table 3, each model contains industry, year, ward dummies and the age of buildings in chome and type of buildings in chome. Standard errors are in parentheses and ***, **, * denote hazard ratios that are significantly different from 1 (or coefficients significantly different from 0 in he case of model1) at 99%, 95% and 90% confidence levels, respectively. Model 1 uses a Probit estimation; model 2 uses a parametric (exponential distribution) shared frailty model; model 3 uses a Cox proportional hazards model and separates plant-level damages into 4 individual categories; model 4 does the same and includes time interactions; model 5 uses a Cox proportional hazards model and separates both plant-level damage and chome damage into 4 individual categories with time interactions.

Table 6. Plant Damage Hazard Ratios for Unproductive, Small, Young and Low-Skill Plants.

	FULL SAMPLE	Least Productive (TFP)	Least Productive (Lab Prod)	Smallest	Youngest	Low-Skill
PlantDAM	3.83***	5.68***	5.01***	8.02***	3.41***	8.29***
	(0.72)	(2.16)	(2.01)	(2.97)	(2.14)	(1.98)
*PlantDAM*Time*	0.83***	0.74***	0.80***	0.77***	0.83***	0.71***
	(0.027)	(0.057)	(0.05)	(0.055)	(0.054)	(0.055)
LR Test		12.27	12.21	15.91	4.46	23.15
(p value)		(0.007)	(0.007)	(0.001)	(0.22)	(0.000)
Observations	16,658	4164	4164	4164	4164	4164

Each model contains controls for 3-digit industry, year, ward, age of buildings in a chome and type of buildings in a chome and all of the other control variables reported in Table 3, column 7.
Standard errors are in parentheses and ***, **, * denote hazard ratios that are significantly different from 1 at 99%, 95% and 90% confidence levels, respectively
Where unproductive, small, young and low-skill plants refer to the lowest quartile of plants in terms of TFP, labor productivity, size, age and skill-level (wage)

Table 7. Determinants of TFP and Labor Productivity 1992-2007 (fixed effects panel)

	1 TFP	2 TFP	3 logLabProd	4 logLabProd
PlantDAM	0.022	0.10***	0.017	0.093**
	(0.025)	(0.027)	(0.023)	(0.035)
*PlantDAM*Time*		-0.0012***		-0.011***
		(0.0024)		(0.0035)
ChomeDAM	0.0042	-0.0090	0.039	-0.039**
	(0.022)	(0.023)	(0.030)	(0.020)
*ChomeDAM*Time*		0.0018		0.011***
		(0.0029)		(0.0015)
WAGE	0.0017***	0.0017***	0.0016***	0.0016***
	(0.00011)	(0.00011)	(0.00013)	(0.00013)
MULTI	-0.057***	-0.058***	-0.077***	-0.077***
	(0.015)	(0.015)	(0.023)	(0.022)
RECON	0.074***	0.074	0.045***	0.044***
	(0.010)	(0.010)	(0.012)	(0.012)
ClusterPlants	0.00065*	0.00064*	0.00036	0.00036
	(0.00036)	(0.00036)	(0.00029)	(0.00028)
observations	11,688	11,688	11,688	11,688
R^2	0.10	0.10	0.14	0.14

Each model contains plant and year fixed effects.
Standard errors are in parentheses and ***, **, * denote coefficients that are significantly different from 0 at 99%, 95% and 90% confidence levels, respectively

Table 8. The Determinants of Plant Births 1993-2007 (negative binomial estimation)

	1	2	3	4
ChomeDAM	-0.96***	-0.93***		
	(0.20)	(0.23)		
*ChomeDAM*Time*		-0.0052		
		(0.020)		
ChomeDAMPink			-0.37	0.50
			(0.34)	(0.41)
ChomeDAMRed			0.61**	1.43***
			(0.32)	(0.39)
ChomeDAMOrange			-1.37***	-1.66***
			(0.46)	(0.58)
ChomeDAMYellow			-0.74**	-0.31***
			(0.33)	(0.41)
*ChomeDAMPink*Time*				-0.14***
				(0.041)
*ChomeDAMRed*Time*				-0.12***
				(0.032)
*ChomeDAMOrange*Time*				0.045
				(0.056)
*ChomeDAMYellow*Time*				-0.062
				(0.038)
RECON	-1.34***	-1.34***	-1.25***	-1.38***
	(0.17)	(0.17)	(0.28)	(0.19)
PLANTS	-0.0048	-0.0047	-0.0046	-0.0052
	(0.0047)	(0.0049)	(0.0047)	(0.0048)
Time		-0.44***		-0.42***
		(0.14)		(0.14)
observations	10,440	10,440	10,440	10,440
Wald	598.2***	597.3***	593.4***	614.5***

Each model contains chome and year effects
Standard errors are in parentheses and ***, **, * denote coefficients that are significantly different from 0 at 99%, 95% and 90% confidence levels, respectively

Appendix

Table A1. Variable Definitions[1]

Variable	
DISTEPI	Distance of plant to earthquake epicenter in kilometres.
SHAKE	Estimated peak ground velocity in centimetres per second estimated at the 250m grid cell level by Fujimoto and Midorikawa (2002).
SMOOTH	A spatially smoothed measure of plant damage (average damage of plants within 100m excluding own building damage).
PlantDAM	Building-level damage index.
ChomeDAM	Chome-level Building damage index.
AGE	The age of the plant in years in 1995.
SIZE (EMP)	The total level of employment at the plant.
SIZE1to SIZE4	Dummy variables =1 if a plant is in the first, second, third or fourth quartiles of total employment, respectively.
WAGE	The average annual wage per worker at the plant 10,000 Yen.
TFP	Total factor productivity, as defined in the online appendix.
MULTI	A dummy variable =1 if a plant is from a multi-plant firm.
RECON	A dummy variable =1 if a plant is located within one of 523 priority reconstruction districts in which reconstruction costs were subsidised and regulations were reduced.
Births	The number of new plants born within a chome.
ClusterPlants	The number of plants belonging to the same 2 digit industry as the plant in question and within the same chome.
ClusterPlantsNb	The number of plants belonging to the same 2 digit industry as the plant in question and within the same chome or neighboring chomes.
ClusterEmp	The level of employment within the same 2 digit industry as the plant in question and within the same chome.
ClusterEmpNb	The level of employment within the same 2 digit industry as the plant in question and within the same chome or neighboring chomes.
VA	The level of value added in 10,000 Yen.
LabProd	The level of value added per worker in 10,000 Yen.
BUILDpre45	Share of buildings built pre 1945 by chome.
BUILD46-55	Share of buildings built 1946-55 by chome.
BUILD56-65	Share of buildings built 1956-65 by chome.
BUILD66-75	Share of buildings built 1966-75 by chome.
BUILD76-85	Share of buildings built 1976-85 by chome.
BUILDafter86	Share of buildings built after 1986 by chome.
BUILDbrick	Share of brick built buildings by chome.
BUILDrconc	Share of reinforced concrete buildings by chome.
BUILDsteel	Share of steel buildings by chome.
BUILDwood	Share of wooden buildings by chome.

[1] All monetary variables are expressed in year 2000 prices.

Variables *SIZE, WAGE, MULTI, MOVE, VA* and *LabProd* come from the Manufacturing Census (Japanese Ministry of Economy, Trade and Industry). Variable *AGE* is from the Establishment and Enterprise Census (Japanese Ministry of Internal Affairs and Communications). Our damage, building age and building type variables are from 'Shinsai Hukkou Akaibu' (archive on the damage of the 1995 Hyogo-Awaji earthquake) by Kobe City Office and Toru Fukushima (University of Hyogo), together with 'Zenrin's Residential Map, Hyogo-ken Kobe city 1995' from Toru Fukushima (University of Hyogo).

Table A2. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
DISTEPI	18.6	13.5	5.7	435.3
SHAKE	79.3	6.4	32.3	93.0
SMOOTH	0.20	0.19	0	0.75
PlantDAM	0.22	0.27	0	0.75
ChomeDAM	0.59	0.25	0.12	1
AGE	18.1	15.0	1	42
SIZE (EMP)	33.2	206.0	3	5673
WAGE	355.9	174.4	67.8	1762.2
TFP	4.40e-12	0.68	-6.9	3.5
MULTI	0.14	0.33	0	1
RECON	0.40	0.49	0	1
Births	0.13	0.67	0	35
ClusterPlants	1.5	3.0	0	20
ClusterPlantsNb	5.1	8.5	0	88
ClusterEmp	53.8	276.3	0	5687
ClusterEmpNb	127.0	410.4	0	5712
VA	69164.6	787135.5	1151.7	3.24e+07
LabProd	954.4	1270.6	3.56	19085.6
BUILDpre45	0.13	0.18	0	0.89
BUILD46-55	0.058	0.071	0	0.46
BUILD56-65	0.17	0.15	0	1
BUILD66-75	0.29	0.19	0	1
BUILD76-85	0.16	0.15	0	1
BUILDafter86	0.18	0.19	0	1
BUILDbrick	0.25	0.16	0	0.65
BUILDrconc	0.22	0.15	0	0.64
BUILDsteel	0.28	0.27	0	1
BUILDwood	0.23	0.20	0	0.99

Number of observations = 16,658